An Automatic Finite-Sample Robustness Metric for Bayes & Beyond: Can Dropping a Little Data Change Conclusions?

Speaking today:
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Work with:
Rachael Meager (LSE)

When can I trust my data analysis?

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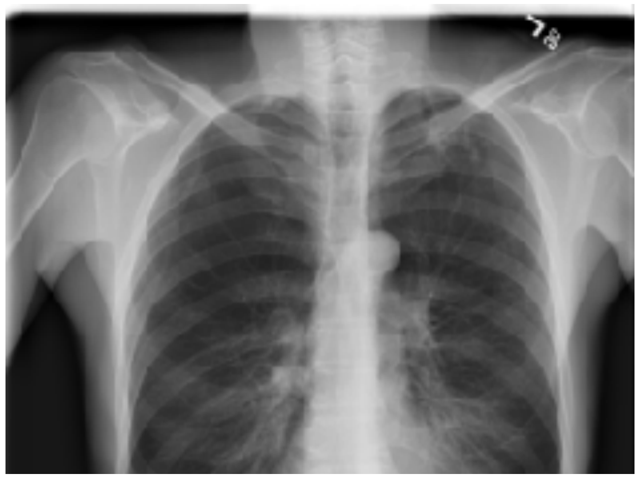

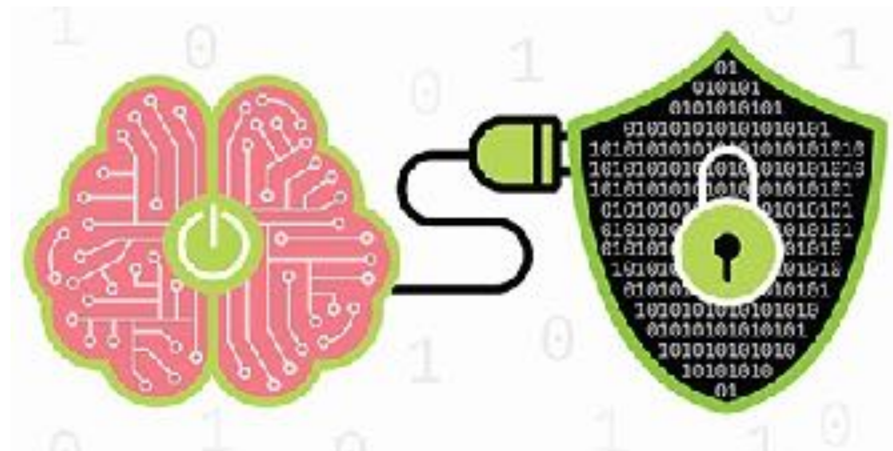

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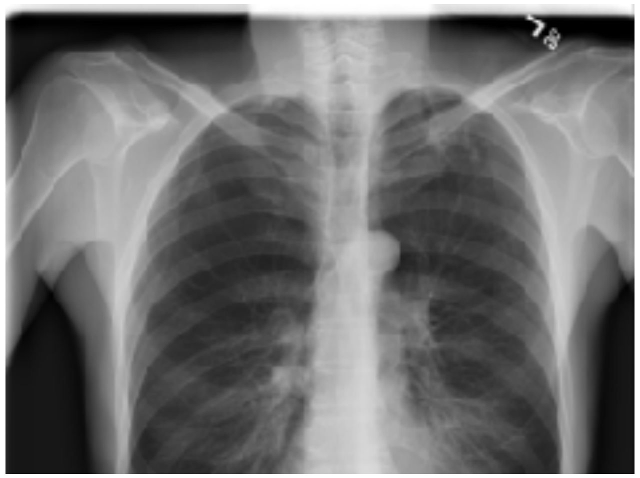

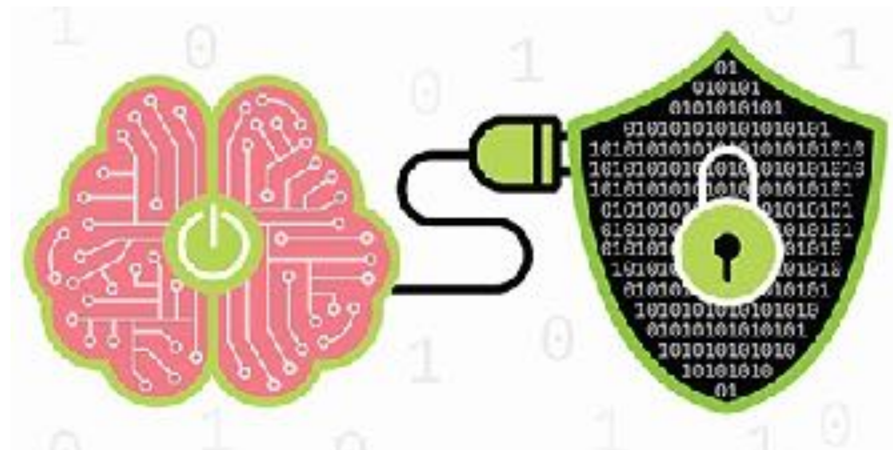

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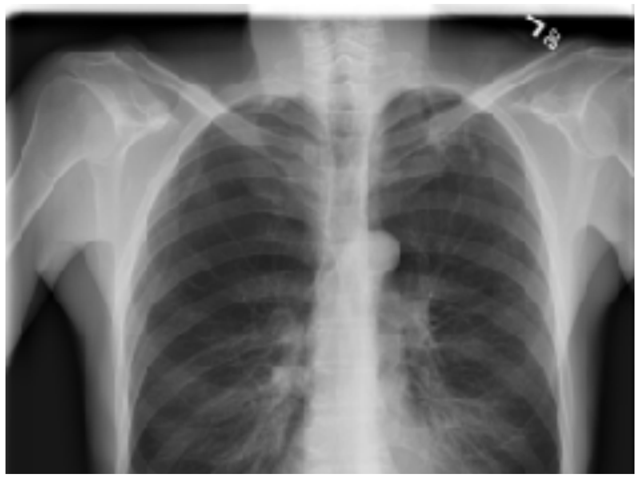

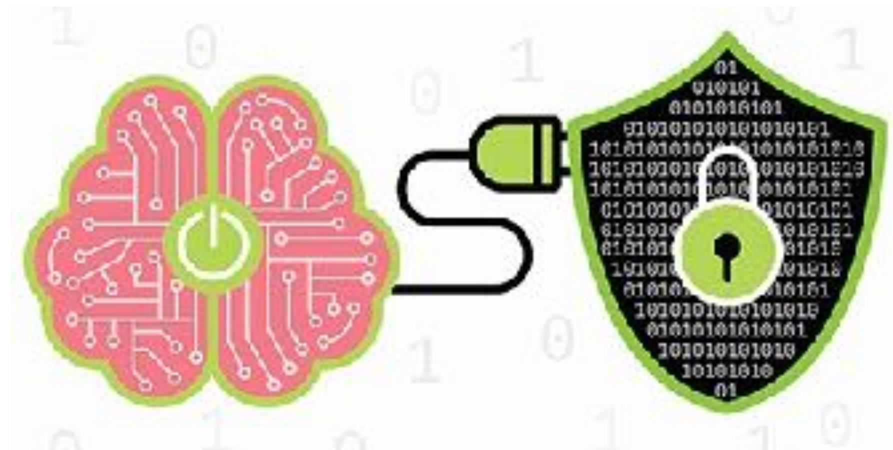

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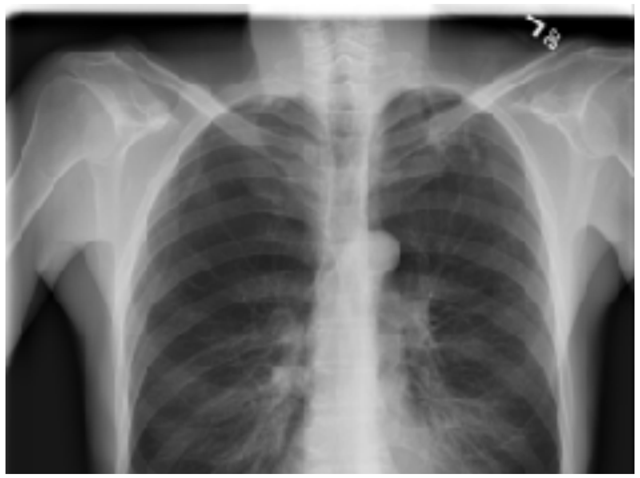
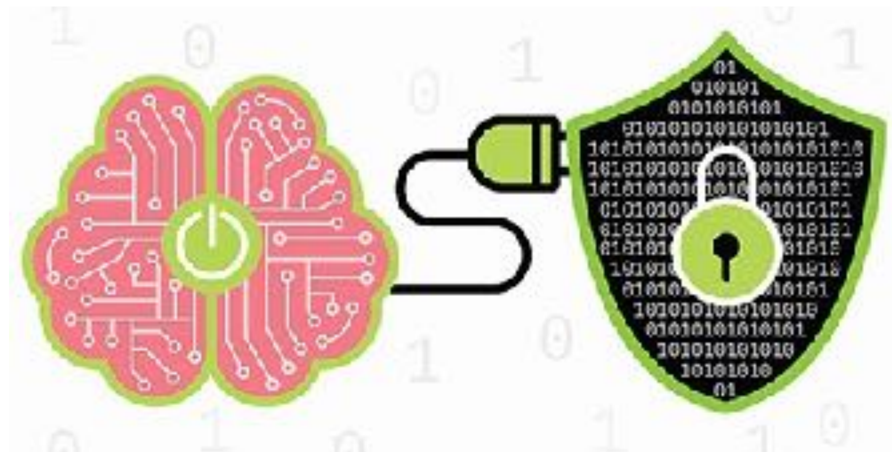


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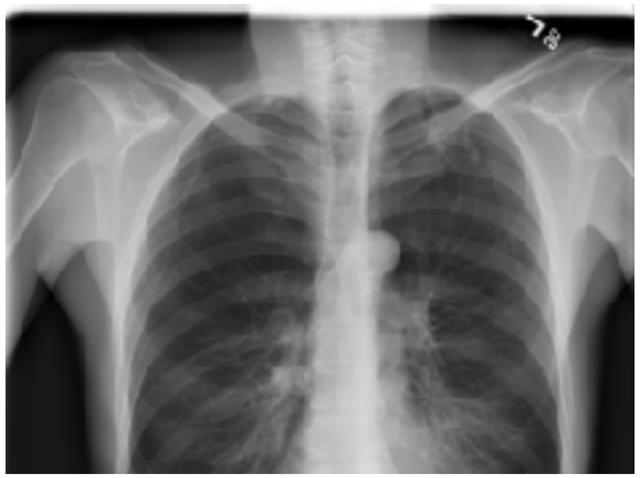

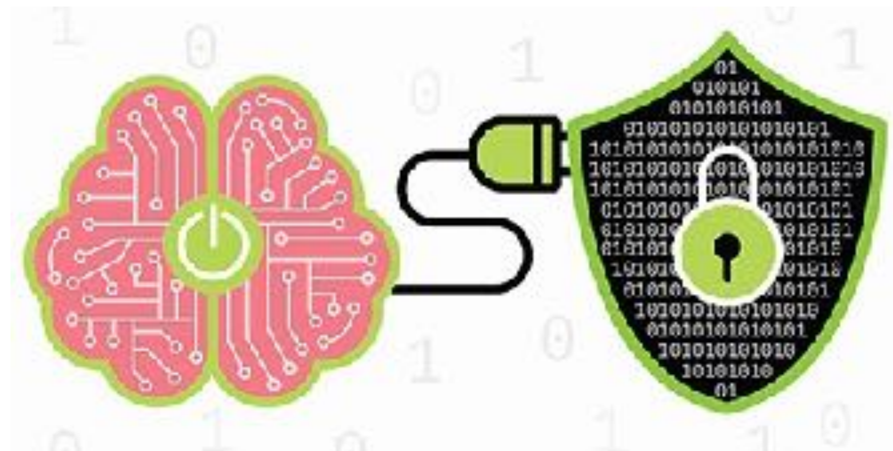

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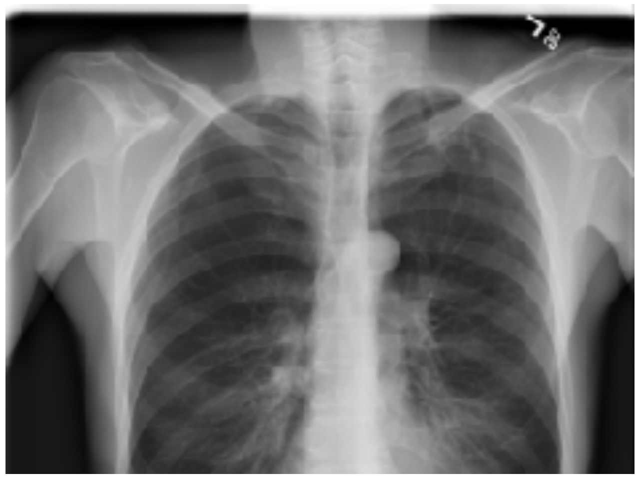

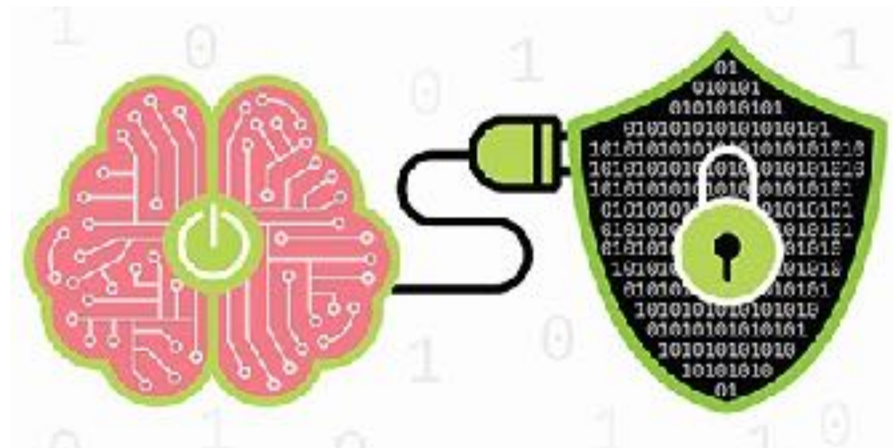

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- **Our Solution**: a fast, automated, accurate *approximation*

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        - Scenario two: You want to recommend your farming methods to a friend across the valley.
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  - But these concerns and our techniques are much more general

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    - Works for variational Bayes, MAP, MLE, OLS, etc.
        - All minimizers of smooth empirical loss!

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  - We find that dropping < 0.1% of data changes the sign of the posterior expected average effect of microcredit
    - Similar sensitivity to the OLS analyses!

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- We show that, in general, sensitivity to dropping small data subsets is:
    - Not primarily driven by misspecification, small sample sizes, or gross outliers
    - Is primarily driven by a low “signal to noise ratio”

Conclusions

- We develop a fast way to check if there is a very small fraction of data you can drop to change conclusions
  - **"An Automatic Finite-Sample Robustness Metric: When Can Dropping a Little Data Make a Big Difference?" https://arxiv.org/abs/2011.14999**

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